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## Editorial

## A unique timely moment for embedding intelligence in applications

Current IT society is populating the planet with a plethora of applications at an unprecedented rate pushed by advances in fabrication, mechatronics and communication technologies on one hand and availability of sophisticated sensor and actuator devices on the other [1]. Applications, that both target everyday life, industrial and mission critical needs, are either confined at a single target device or distributed within a network of units, by also taking advantage of seamless communication capabilities and address different application scenarios. Examples of this trend are the Internet-of-Things, smart-whatsoever (home, grid, building, city, planet) and cyber-physical systems [2].

Such units/agents mostly interact with the environment they are placed in through sensors and actuators, hence setting the technological bases for the cyber-physical framework. In some cases, sensors and actuators can be virtual, in the sense that the physical entity is not there but datastreams are coming and decisions suitably taken based on their information content (an example of a virtual sensor is, for instance, the “like/unlike” button on social networks).

Moreover, the pervasive dissemination of units, their volume and the necessity to satisfy ever increasing demands for autonomy, energy-awareness and reliability has led application designers and researchers to move towards the autonomic computing paradigm [3,4] requesting the units to be able to support self-configuration, management, healing and protection functionalities [5].

The crucial shift in the operational paradigm is that the environment and, then, the user, are now explicitly considered part of the functional model; reactions are then issued in response to changes in the system or variations in the operational environment. Straightforward examples in this direction are the human-robotic co-working, where humans and robots cooperate together, at the same time, to solve a complex task (e.g., within a car assembly isle) or the smart-grid where information coming from the field is processed within a Machine-to-Machine (M2M) or Human-to-Machine (H2M) framework to provide an immediate feedback and reaction to the requested power demand.

What is somehow missing in current technologies is the ability of these units to provide fully harmonized intelligent abilities, with a significant research effort needed to move ahead and guarantee that our applications do what they are supposed to do in an appropriate way within an uncertain, mostly unspecified and time variant framework [5].

By focusing on machine perception, human–computer interaction, intelligent information processing, network intelligence and mobile computing, decision-making and intelligent control, robotics and intelligent systems the CAAI Transactions on Intelligence Technology comes timely, appropriate and mostly requested. At the same time it represents the most welcome venue and forum for addressing and advancing above scientific and technological challenges.

This editorial would fail if attempting to tell the researcher which areas of artificial or computational intelligence to focus in. The main reason being that there are so many relevant fields and open problems that very few should be preferred than others provided that an accurate scientific method is carried out and that what proposed aims at either advancing basic theory or solving a true real problem. In both cases, we should pay attention to the impact of what we are proposing, its novelty content as well as provide a sound, comprehensive state of the art. We should refrain from looking at the last 5 years literature only by keeping in mind that major results in the topics we are researching in –and this Transactions is hosting- date back as early as the middle of the last century.

The above said, not rarely in doing our research, we make assumptions whose validities are mostly confined to the laboratory and hold only in particular –though relevant- real world cases. My invitation here is therefore to advance research by trying to remove –or attempting to weaken- those assumptions. I will try to make the point in the sequel by presenting, without the pretention of being exhaustive, some assumptions that we do currently assume in our research. To me, weakening each of those would represent –per se- a major research achievement.

- Stationarity/time invariance

In designing our applications we mostly assume that incoming data are stationary, i.e., the process generating the

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data provides a sequence of i.i.d. realizations of a unique random variable whose distribution does not change with time. As such, stationarity applies to stochastic processes and is a common made hypothesis in machine learning, fuzzy systems design (e.g., in designing the fuzzy controller) and evolutionary optimization (e.g., the optimizing process). As an extension of stationarity we say that a process is time invariant when its outputs do not explicitly depend on time [5]. Less formally, in the former case the probability density function does not change with time, in the latter, the transfer function of the -possibly dynamic- system does not have an explicit time dependency. Unfortunately, such amenable hypotheses are hardly met in real applications and, in the best cases, they represent a first order approximation of reality. Even though important results have been achieved in last years, e.g., see [6] for a survey, much research work is needed to be able to advance our systems towards the intelligence technology paradigm current applications are requesting for.

Removal of this strong hypothesis leads to the “Learning in a nonstationary environments” framework. Here, intelligent solutions working on datastreams and processing their information content must be able to detect –possibly anticipate-, and identify the occurrence of time variance (e.g., type, magnitude, time occurrence of the change), its impact on the application and react accordingly by adapting the application over time in order to remove/mitigate the effect of change and grant high performance.

- Data correctness

Most of applications are assuming that acquired data are correct i.e., fault free. However, not rarely, collected data are incomplete (in the sense that some or multiple instances are missing) or do not make sense for various reasons (e.g., the electronic readout was affected by a transient or a permanent fault) [7]. In turn, wrong data mostly imply wrong information that, once fed into our application, leads to erroneous decisions. In most severe cases this might lead to dramatic outcomes. The data correctness assumption is mostly implicitly taken as granted and many researchers assume that data are correct and “true” by definition.

This assumption does not surely hold in many applications, and hardly is met in Big Data framework (the possibly low probability of fault occurrence affecting the incoming data is contrasted by their large cardinality). Here, the investigation has to design a new family of computationally light and effective “model-free fault diagnosis systems” for embedded application. Fault detection, identification, isolation and possibly mitigation steps need to be considered to identify and host the occurrence of transient and permanent faults that might affect both sensors and actuators within a networked environment.

- Deterministic computation

Within an intelligence technology framework we design our applications within (partly) unspecified, highly uncertain

environments and mostly rely on computational intelligent techniques to solve them. In such uncertainty environment we identify a solution among a set of possible similarly performing –but different- solutions, with each solution affected by uncertainty itself at different level. Consider, for example, a non-linear regression problem where at first you need to select a hierarchy of model families (e.g., a feed-forward neural network family of models), then a family of model (e.g., obtained by fixing the topology of the network as well as the type of non-linearity), and finally determine the model (i.e., we set the parameters). All above steps are affected by uncertainty: I might consider different hierarchies (e.g., feed-forward backpropagation, Radial Basis Functions, recurrent architectures), use different training algorithms and methods, each of which yielding a different solution. Then, we assess the performances of the models and select the one we mostly like among many others which, once assessed through sound statistical tests emerge to be equivalent in terms of performance (the claim is even stronger once we configure our solution starting from a small or unbalanced training dataset). The question we should ask ourselves is “given the highly uncertainty that led to a given model whereas many others might have been selected, does it make sense to introduce a deterministic computation where many computational efforts are spent to generate the solution output”?

It comes out that the high computational burden requested by the solution solving the application—mostly required in order to address sophisticated tasks-, neither requires to be executed in a deterministic way nor by complex algorithms. The former aspect leads to consider approximate computing devices, the latter approximate or incremental algorithms balancing computational complexity with accuracy and response time (e.g., high accuracy is achieved at the expenses of a higher computational effort) [8].

Removal of the deterministic computation hypothesis leads to the concepts of probabilistic and approximate computing, e.g., a fuzzy approach.

Most of the above research lines are still in a very embryonic state with the related literatures proposing solutions focusing on particular aspects: a comprehensive approach is however missing and constitutes a fertile research land and the right place where to consider intelligent—model or reference free- computational paradigms.

I encourage readers and contributors to this new journal to face these major research problems in their respective Artificial and Computational Intelligence research fields and advance all those existing problems and challenges that require intelligence and intelligent technologies.

I am sure that the CAAI Transactions on Intelligence Technology will constitute a unique forum bringing together researchers at one platform to share knowledge, information and practical experience gained in their specific research discipline.

As Science is meant for innovation, creativity and problem solving I welcome this new journal with my best wishes and forecast a unique prestige that only your excellent contributions as authors and readers can provide.

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Prof. Cesare Alippi, PhD, IEEE Fellow\*

*Dipartimento di Elettronica, Informazione e Bioingegneria,  
Politecnico di Milano, Italy*

*Università della Svizzera Italiana, Switzerland*

\*Dipartimento di Elettronica, Informazione e Bioingegneria,  
Politecnico di Milano, Piazza L. da Vinci 32, 20133 Milano,  
Italy. Tel.: +39 02 23993512.

*E-mail address:* [cesare.alippi@polimi.it](mailto:cesare.alippi@polimi.it).

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